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1 **Physical predictors of elite skeleton start performance**

2 *Original Investigation*

3

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Abstract

Purpose: An extensive battery of physical tests is typically employed to evaluate athletic status and/or development often resulting in a multitude of output variables. We aimed to identify independent physical predictors of elite skeleton start performance overcoming the general problem of practitioners employing multiple tests with little knowledge of their predictive utility. **Methods:** Multiple two-day testing sessions were undertaken by 13 high-level skeleton athletes across a 24-week training season and consisted of flexibility, dry-land push-track, sprint, countermovement jump and leg press tests. To reduce the large number of output variables to independent factors, principal component analysis was conducted. The variable most strongly correlated to each component was entered into a stepwise multiple regression analysis and *K*-fold validation assessed model stability. **Results:** Principal component analysis revealed three components underlying the physical variables, which represented sprint ability, lower limb power and strength-power characteristics. Three variables, which represented these components (unresisted 15-m sprint time, 0-kg jump height and leg press force at peak power, respectively), significantly contributed ($P < 0.01$) to the prediction ($R^2 = 0.86$, 1.52% standard error of estimate) of start performance (15-m sled velocity). Finally, the *K*-fold validation revealed the model to be stable (predicted vs. actual $R^2 = 0.77$; 1.97% standard error of estimate). **Conclusions:** Only three physical test scores were needed to obtain a valid and stable prediction of skeleton start ability. This method of isolating independent physical variables underlying performance could improve the validity and efficiency of athlete monitoring potentially benefitting sports scientists, coaches and athletes alike.

Key words: athletes, testing, multivariate, PCA, validation.

Introduction

Sport scientists and coaches often endeavour to establish the key physical determinants of elite sports performances with the aim of optimising training strategies and maximising chances of success in competition. A fast start is widely considered to be a prerequisite for a successful performance in ice-track sports.^{1,2} Accordingly, previous descriptive studies have attempted to identify some key performance indicators in skeleton,³ bobsleigh⁴ and luge⁵. For example, vertical jump and sprint performance measures were reported to be the most valuable predictive assessment for identifying superior starters in US national skeleton³ and bobsleigh⁴ teams. For this reason, strength and power training are the main focus of preparation for skeleton athletes and various physical tests are typically incorporated into athlete monitoring programmes. Indeed, previous work suggested that successful skeleton talent identification and development models should be centred around these tests.⁶

It is likely, however, that different physical measures obtained through physical testing batteries overlap in terms of which aspect of performance is being measured. This is a common challenge faced in practically all sports, as independent predictors of performance have seldom been identified. Such information is crucial to effectively and efficiently quantify an athlete's status and/or development, and to ensure that personalised training practices are focussed to improve the key qualities influencing performance outcomes.

The aims of this study were to identify a set of independent physical characteristics which are fundamental to a fast skeleton start and investigate the variability of such physical tests and performances over a training season.

74

75 **Methods**

76 *Participants*

77 Thirteen (eight male, five female; mean age \pm SD = 24 \pm 2 yr) national squad skeleton
78 athletes participated in this study and provided written consent prior to data collection.

79 The study was conducted in accordance with the principles of the Declaration of
80 Helsinki⁷ and a local university research ethics committee provided ethical approval.

81

82 *Data collection and processing*

83 Data were collected across an average of five 2-day testing sessions during a 24-week
84 summer training season. Each athlete was scheduled to complete five different physical
85 tests at each testing session (in the order of flexibility, push-track and sprint testing on
86 the first testing day and countermovement jump and leg press testing on the second
87 day). Testing schedules were consistent across all sessions and athletes were asked to
88 refrain from vigorous exercise for 36 hours before testing. These sessions coincided
89 with the beginning and end of a four- or eight-week training block. Some athletes were
90 unable to complete all tests at every time point due to injury, illness or technical
91 difficulties, however, 59 complete data sets were obtained.

92

93 *Push-track*

94 Athletes completed and documented an individual 30-minute warm-up at the first data
95 collection session, which was replicated at subsequent sessions. Three maximum effort
96 push-starts were performed on an outdoor dry-land push-track with a three-minute
97 recovery between runs. The 38- and 45-m split times were recorded by a permanent
98 photocell system (Tag Heuer, Switzerland; 0.001s resolution) and used to calculate

average velocity (V_{38-45}) over this section, before which athletes have always loaded the sled (Figure 1). Additional photocells (Brower Timing System; Utah, USA; 0.001s resolution) were placed 14.5 and 15.5 m from the starting block providing 15-m sled velocity (V_{15}). These performance measures were selected based on previously documented associations between similar measures and overall ice-track start performance.⁸

Flexibility

A trained physiotherapist conducted two knee extension flexibility tests with the hip flexed at 90° and 110° to the horizontal. These were conducted from a supine position with the contralateral leg fixed to a bench. The hip joint was flexed to the respective angle before the knee was passively extended upwards until a strong hamstring stretch was felt. Knee angle was recorded using a manual goniometer with the axis placed on the knee joint centre of rotation and the arms aligned along the lateral midlines of the thigh and shank. High intra-tester reliability has previously been documented for similar knee flexion/extension measurements.⁹ Additionally, sit and reach tests were conducted whereby athletes maintained full knee extension and flat foot contact with a sit and reach box (Body Care, Warwickshire, UK) and maximum reaching distance was noted. Two knee extension flexibility scores for each leg (at each angle) and three sit and reach scores were recorded.

Sprint

Athletes performed three maximal 30-m unresisted sprints and three maximal 30-m resisted sprints on an indoor synthetic running track from a three-point starting position with a three-minute recovery between runs. The resistance (10 kg for males and 7.5 kg

for females) was provided by a weighted sled connected by a waist-harness and towed behind. Photocells (Brower Timing System; Utah, USA; 0.001s resolution) were placed on tripods on the 15- and 30-m marks at waist height to reduce errors caused by inconsistent body configurations across photocells.¹⁰ Timing was initiated when the hand was released from a touch pad placed on the starting line and split times were recorded.

Countermovement jump

Vertical jump performance was assessed across a series of loads: unloaded (hands remained on hips throughout jump), 5 kg (weight plate held across the chest), 15-kg (females) or 20-kg (male) barbell held across the back of the shoulders and 50% body mass (0.5BM; loaded barbell to the nearest 0.25 kg held across the back of the shoulders). Three jumps were performed at each of these loads with at least a two-minute recovery period between efforts. Longer recovery periods (3-4 minutes) were given between the 50% body mass jumps. Each of these jumps was performed in a squat rack and on a force plate (Fi-tech; Skye, Australia), which sampled vertical ground reaction force data at 600 Hz. The vertical force (Fz) data were filtered using a low-pass second-order recursive Butterworth filter with 82 Hz cut-off frequency derived through residual analyses. For each jump, maximum centre of mass displacement (jump CM_{disp}) was calculated using the impulse-momentum relationship in addition to peak power, mean power and average rate of force development (ARFD, peak force divided by time from start of active force production to peak force).

Leg press

Strength and power characteristics were assessed using a Keiser A420 leg press dynamometer (Keiser Sport, Fresno, CA), which provides force and velocity data (sampled at 400 Hz) across each effort. Starting from a seated position (approximately 90° knee flexion) an incremental test was completed beginning at low resistance and reaching an estimated ‘one repetition maximum’ resistance on the tenth repetition. Athletes were asked to fully extend both legs with maximum velocity, and resistance was increased each repetition until failure (some athletes performed over 10 repetitions). For each effort, peak force, velocity and power were recorded for each leg. A linear trendline was plotted through the peak force-velocity data (Figure 2), as appropriate for this type of exercise.¹¹ The linear trendline was extrapolated to the axes to yield theoretical maximum isometric force (F_{\max}) and maximum velocity (V_{\max}) and the gradient (FV_{grad}) was also recorded to reflect the orientation of the force-velocity profile. A second-order polynomial was fitted through the peak force-power data, the equation of which was numerically differentiated and used to calculate maximum power (P_{\max}) and force at P_{\max} (FP_{\max}). Means were calculated across both legs for all variables, and F_{\max} , P_{\max} and FP_{\max} were normalised for body mass.

Statistical analyses

For the physical tests which included multiple trials (push-track, sprint and countermovement jump), mean values were calculated at each testing session for each athlete. Means and standard deviations were then computed for males and females. Additionally, coefficients of variation (CV) were determined to provide a measure of within-athlete variability in the physical test scores across a training season and subsequently averaged to provide group mean CVs. Test scores were log transformed prior to these CV calculations.

A single mean and standard deviation was also calculated for each individual athlete across all attended testing sessions. Subsequently, Pearson correlation coefficients were used to assess the relationships between these mean physical test scores and both V_{15} and V_{38-45} . Male and female athletes were combined together, as the relationships between physical characteristics and performance were not considered to be gender dependent. For all correlation coefficients, a threshold of 0.1 was set for the smallest practically important effect and 90% confidence intervals (CI) were used to make magnitude-based inferences, as previously advocated.¹²

Determining the degree to which different physical test scores contribute to performance is difficult in an elite sport setting due to the typically large number of output variables and inevitably small sample sizes. Thus, principal component analysis (PCA) was used to explore the underlying structure and reduce the number of physical test scores to a small set of independent components. This multivariate analysis should be conducted with between five and ten times as many observations as variables.¹³ Therefore, to maintain statistical power, the number of variables which were input into the PCA had to be reduced, as 59 data sets were available. When deciding which variables to enter into the PCA, Hair et al.¹³ encourages researchers to consider the foundations of the variables and use judgement to decide which are appropriate for inclusion. Thus, the variables entered were carefully selected based on both the association with push performance and the perceived independence from other selected variables.

Raw data were first transformed into z-scores to standardise scaling and the suitability of the data set for PCA was confirmed (variables were sufficiently correlated) using Bartlett's test of sphericity and Kaiser-Meyer-Olkin measure of sampling adequacy. An initial solution was then computed with the optimum number of components determined using the scree test criterion. An orthogonal rotation (varimax) was used to simplify the matrix structure. Component loadings exceeding ± 0.70 were considered to indicate significant loading¹³ and any cross-loaded variables (equally correlated to multiple components) were eliminated before the analysis was repeated.

When an acceptable solution was obtained, in which all variables had significant loading on a single component, surrogate labels were assigned, which were considered to reflect the loaded variables. The most heavily loaded (most strongly related) variable to each component was then used as a predictor variable in a stepwise multiple regression analysis, in which the criterion was push-track performance. The Durbin-Watson statistic assessed autocorrelation, and consistency of the residuals was evaluated using homoscedasticity and normality tests. Entered variables remained in the model, if a significant R^2 change ($P < 0.05$) was reported.

Ideally, independent data sets are used to robustly validate predictive models, however, this is rarely possible in reality and especially difficult within elite sport. Thus, a K -fold cross-validation technique was adopted to provide a rigorous assessment of model stability.¹⁴ This involves splitting the data into K roughly equal-sized parts, fitting a regression model to $K - 1$ parts and validating this model against the k^{th} part. This process is then repeated for $k = 1, 2, \dots, K$. In the current study, each k^{th} part comprised data for one athlete only and therefore $K = 13$. In this way, no validation data set

included data from athletes who were used to create the regression model. Prediction errors were calculated for K iterations and combined to provide an overall standard error of the estimate (SEE). Additionally, the correlation between predicted and actual V_{15} was computed and compared with the R^2 value of the initial model. Generally, a model can be considered stable, if the R^2 decrease does not exceed 0.10.¹⁵

Results

Many physical performance variables were found to be strongly related to both V_{15} (Figure 3) and V_{38-45} (Figure 4). Eight of these variables (unresisted sprint 15-m time, resisted sprint 15 - 30-m time, jump CM_{disp} under 0-kg load, jump CM_{disp} under 5-kg load, Keiser F_{max} , Keiser P_{max} , Keiser V_{max} and Keiser FP_{max}) were then entered into the PCA. Two (P_{max} and V_{max}) were found to be cross-loaded (across two components) and thus were eliminated from the data set and the analysis was repeated with the six remaining variables. Bartlett's test of sphericity ($P = 0.00$) and the Kaiser-Meyer-Olkin measure of sampling adequacy (0.74) confirmed that the data were appropriate for this analysis. Three components were derived from the PCA (Table 1) explaining a total of 97.2% of the total variance in the data. Components 1, 2 and 3 were considered to represent sprint ability, strength characteristics and lower limb power, respectively.

The variable which was most strongly related to each component was considered to best represent that component and was entered into a stepwise multiple regression analysis. Thus, unresisted sprint 15-m time, Keiser FP_{max} and jump CM_{disp} under 0-kg load were predictor variables and V_{15} was the criterion. The choice of criterion was based on the previously documented high association between 15-m sled velocity and

ice-track start performance.⁸ All three independent variables significantly contributed to the regression model (81, 3, 2% of the variance explained by unresisted sprint 15-m time, Keiser FP_{max} and jump CM_{disp} under 0-kg load; $P = 0.000, 0.000, 0.004$, respectively) and overall, 86% of the variance in V_{15} was explained. Unresisted sprint 15-m time appeared to have greater relative predictive power for V_{15} compared with jump CM_{disp} under 0-kg load and Keiser FP_{max} (standardised β coefficients were -0.712 vs. 0.347 and -0.181, respectively). The unstandardised β coefficients were then used to form the following regression equation:

$$V_{15} = (-1.868 \times \text{unres. sprint 15-m time}) + (0.015 \times \text{0-kg jump } CM_{disp}) - (0.011 \times FP_{max}) + 11.530$$

When the K -fold validation technique was used to evaluate the model, a strong relationship between predicted and actual V_{15} was observed ($r = 0.88$, 90% CI = 0.82 to 0.92; $R^2 = 0.77$). Additionally, the SEE were inflated to a small degree, when the K -fold validation method was applied compared with the original model (0.17 $m \cdot s^{-1}$ and 1.97% vs. 0.13 $m \cdot s^{-1}$ and 1.52%, respectively).

Within-athlete variability in the physical test scores achieved across the training season is presented in Tables 2 and 3. Greater variability was observed in the jump CM_{disp} (CV range = 4.2 - 7.6%) and leg press (3.2 - 16.1%) scores compared with the measures of sprint (1.0 - 2.5%) and push-start (0.9 - 1.5%) performance. In fact, male athletes enhanced maximum isometric force (Keiser F_{max}) by 27.9% and unloaded vertical jump performance by 10.5% across the entire season, whereas 15-m sled velocity increased by only 1.2%. Female athletes exhibited greater improvements in push performance

(V₁₅, 4.4%) across the training period than male athletes, concomitant with large increases in both maximum isometric force (Keiser F_{max}) and jump CM_{disp} under 0-kg load (16.7 and 19.5%, respectively).

Discussion

The advancement in technologies available to sport scientists, coupled with the pressure to achieve a competitive advantage, has resulted in large amounts of data typically being collected, often with insufficient time for analysis and interpretation.¹⁶ In this context, principal component analysis can be a particularly useful tool to assess the underlying structure of data sets and reduce these large number of parameters to a small set of independent components. By combining this with multiple regression analysis, a small number of performance predictors can be obtained which relate to independent attributes. In this study, we aimed to determine the key physical predictor variables of elite skeleton start performance by using this multivariate approach. Three variables (unresisted sprint 15-m time, jump CM_{disp} under 0-kg load and Keiser FP_{max}) emerged as independent predictors of start performance in skeleton athletes explaining 86% of the variance in start performance. These data highlight important areas to target during personalised training and monitoring programmes.

Initial bivariate analyses revealed relationships between start performance and many of the physical test scores (Figures 3 and 4) with the strongest associations observed between unresisted 15-m sprint time and 15-m sled velocity ($r = -0.93$) and between resisted 15 - 30-m sprint time and 38 - 45-m sled velocity ($r = -0.88$). In both cases, faster sprint times were associated with better push-start performance. Increased jump CM_{disp} and peak power under 0-kg and 5-kg loads were also strongly related to superior push-start performance suggesting that power production under lighter loads (and

therefore higher velocities) is potentially more important to push performance than under heavier loads (and lower velocities). These associations are consistent with those previously shown amongst US skeleton³ and bobsleigh⁴ athletes. Additionally, the successful four female athletes from an Australian skeleton talent identification programme were those who recorded faster 30-m sprint times and higher unloaded jump powers at the initial screening.⁶ This provides further evidence that sprinting abilities transferred to fast starts provide large chances of success in this sport, as indicated previously.²

Generally, it is likely that some of these physical tests measured similar performance factors. Through simple linear regression, it was unclear whether different test scores independently contributed to performance. For this reason, PCA was used in this study to extract three independent components (labelled sprint ability, lower limb power and strength-power characteristics), which were subsequently found to significantly contribute to the regression model (86% variance in V_{15} explained). When the K -fold validation technique was adopted, the model was shown to provide a sufficiently stable prediction of push-track performance from just three variables. Such findings have clear implications for monitoring skeleton athletes, but can also play an important role in talent identification schemes by highlighting the most important attributes for athletes to possess, and potentially reducing the number of tests conducted.

In line with the bivariate analyses, the regression model found sprint ability to explain the largest portion of the variance (81%) in push-track performance. Although the relative contributions to the prediction were small, jump CM_{disp} (0-kg load) and force-power characteristics (Keiser FP_{max}) both made significant contributions (3 and

2%, respectively) to the prediction and the associated tests are therefore worthwhile inclusions in the testing battery. Interestingly, the force at peak power (Keiser FP_{max}) negatively contributed to the model supporting the above previous finding that achieving peak power under lighter loads is important to skeleton start performance. In fact, high contraction velocity (V_{max}) was a more important determinant of skeleton start performance ($r = 0.62$) than maximum isometric force (F_{max} ; $r = 0.39$). This finding is in agreement with research in athletics, where faster sprinters were found to elicit a more ‘velocity-oriented’ force-velocity profile obtained using an instrumented treadmill.¹⁷ Moreover, these findings support previous suggestions that explosive performance is determined by both power maximisation and the optimisation of force-velocity characteristics.¹⁸

In elite sport research the number of athletes available is inevitably small and it is difficult to achieve a sufficiently high sample-to-predictor ratio for multivariate analyses. Thus, to truly obtain insight regarding elite performance, the only realistic option is sometimes to pool the data, as in this study. Combining multiple data points from individuals may introduce some dependence and clustering of residuals, which could potentially compromise the statistical rigour of this procedure. However, to ensure this was not the case in the current study, several tests (including Durbin Watson and heteroscedasticity tests) were used to robustly assess for excessive autocorrelation and inconsistent residuals, as recommended.¹⁹ Future studies adopting similar methodology should carefully assess the suitability of the data set by performing these rigorous checks.

An intensive 24-week training period appeared to induce changes in all physical measures with intra-athlete variability observed in the scores achieved. Greater changes in strength and power indices were exhibited compared with the changes in push and sprint performance measures. For example, an increase in unloaded jump performance of 10.5% was observed across the entire training season, whereas 15-m sled velocity improved by only 1.2% in male athletes. This aligns with previous findings that large training-induced gains in strength and power have only small influences on sprint-based performances in moderately trained individuals²⁰⁻²³ and elite rugby players²⁴. Nonetheless, as skeleton races can be decided by only 0.01 seconds in some cases²⁵, the push-start improvements observed could be meaningful.

Practical Applications

This study has introduced a process through which to evaluate testing batteries and extract independent variables which underpin performance. Principal component analysis is rarely used in sports science to overcome the issues faced when collecting and interpreting large numbers of output variables in naturally small populations. This is especially the case in elite sport science research, such as this study. Additionally, the *K*-fold validation allows robust evaluation of model stability in this setting, where an independent validation data set is not available. It is encouraged that this method is adopted across other sports to better understand the physical determinants of performance, and potentially improve the efficiency of talent identification and athlete monitoring protocols.

Conclusions

370 This study adopted a systematic series of multivariate analyses to identify three
371 independent variables, which together explained 86% of the variance in elite skeleton
372 start performance. These variables (unresisted sprint 15-m time, jump CM_{disp} under
373 0-kg load and Keiser FP_{max}) can be categorised as testing sports-specific aspects of
374 lower-limb speed, explosive power and strength characteristics and were shown to
375 provide an accurate and stable prediction of skeleton start performance. Therefore, the
376 importance of physical tests, when monitoring skeleton athlete development, is evident.
377 The above predictors should be used to personalise skeleton athlete training
378 programmes and monitor the efficacy of training. Additionally, the described
379 methodology could also be used within other sports, particularly where the number of
380 truly elite participants is limited.

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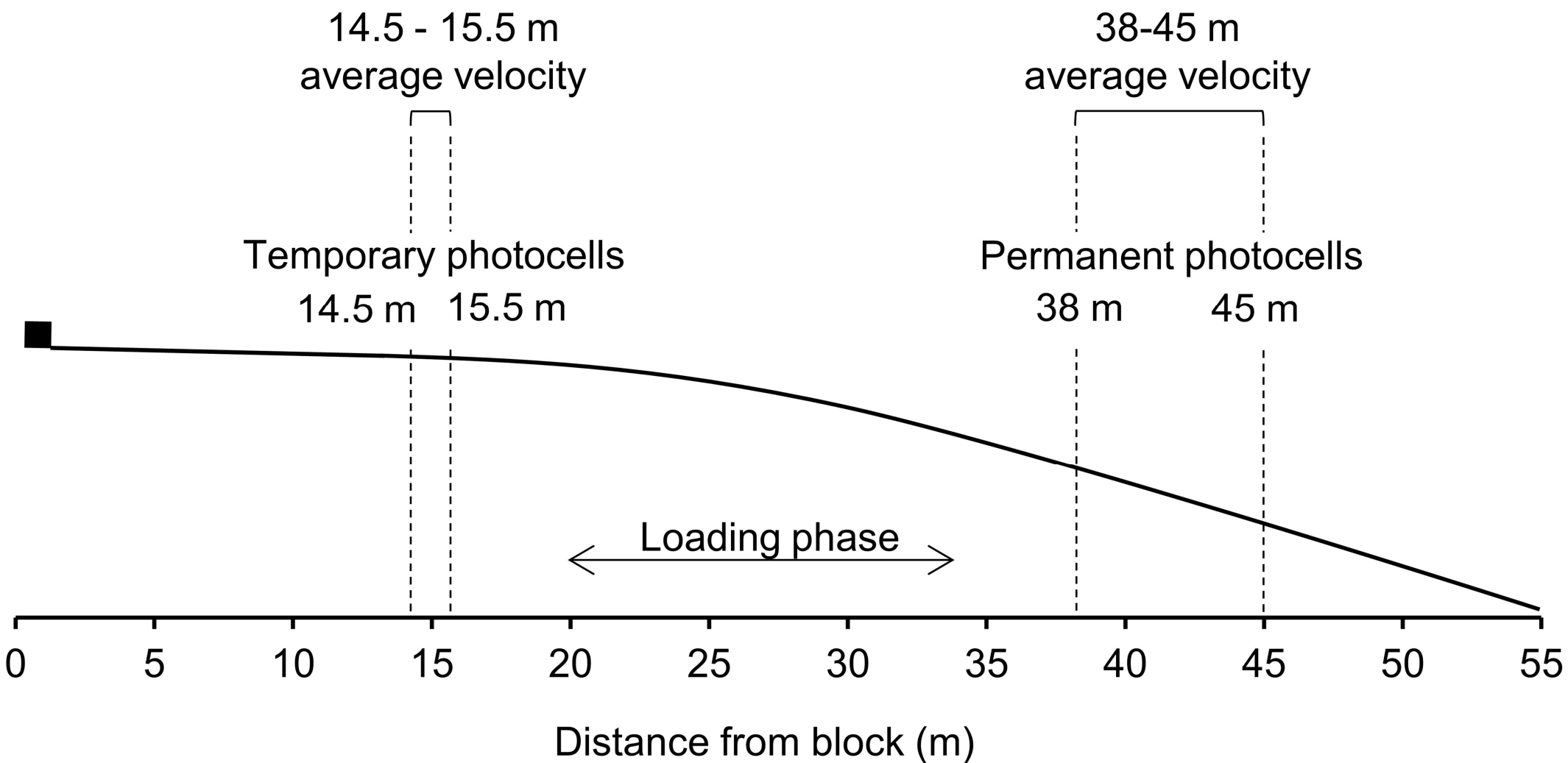
Figure Captions

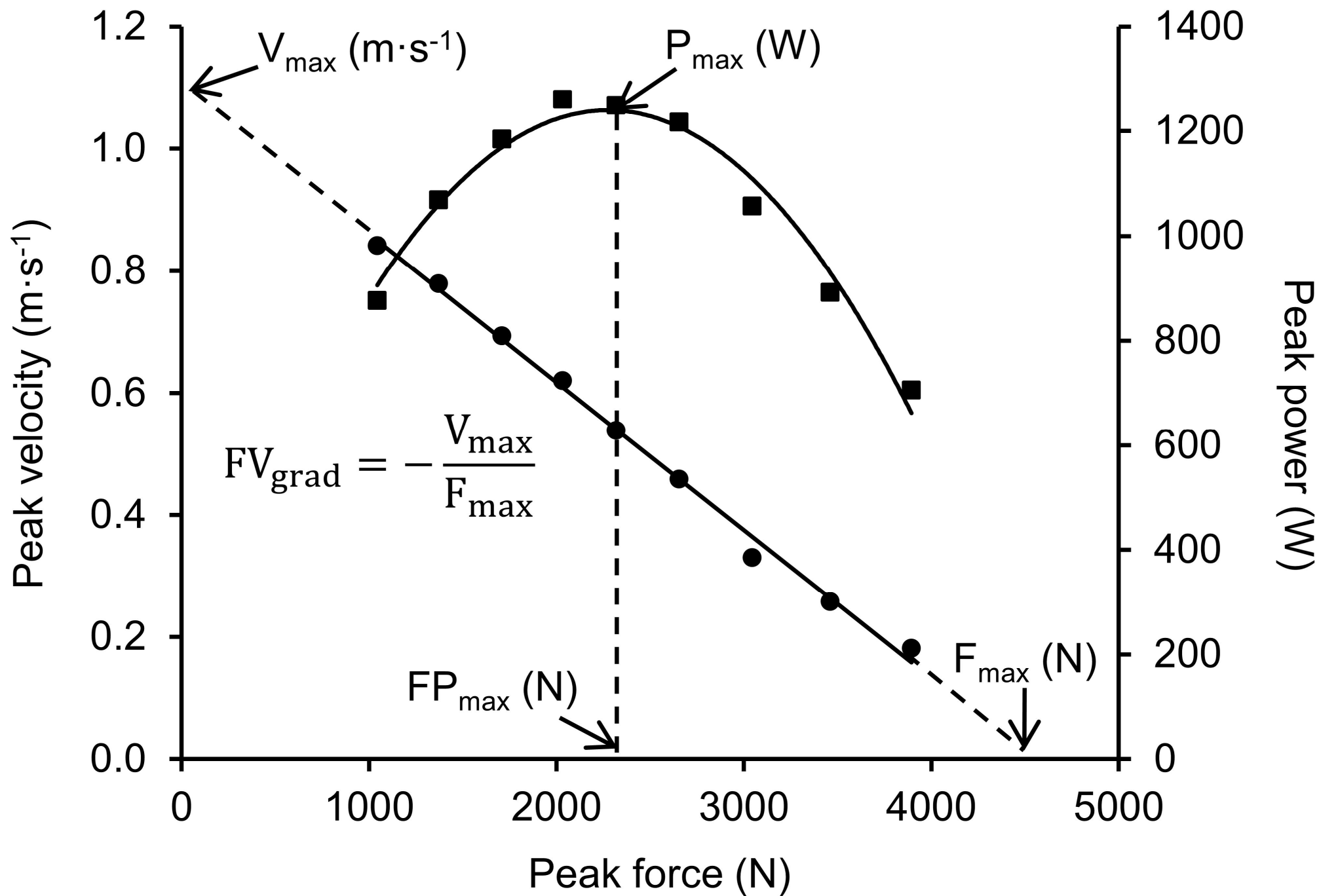
Figure 1. Schematic representation of the push-track set-up and start performance outcome measures.

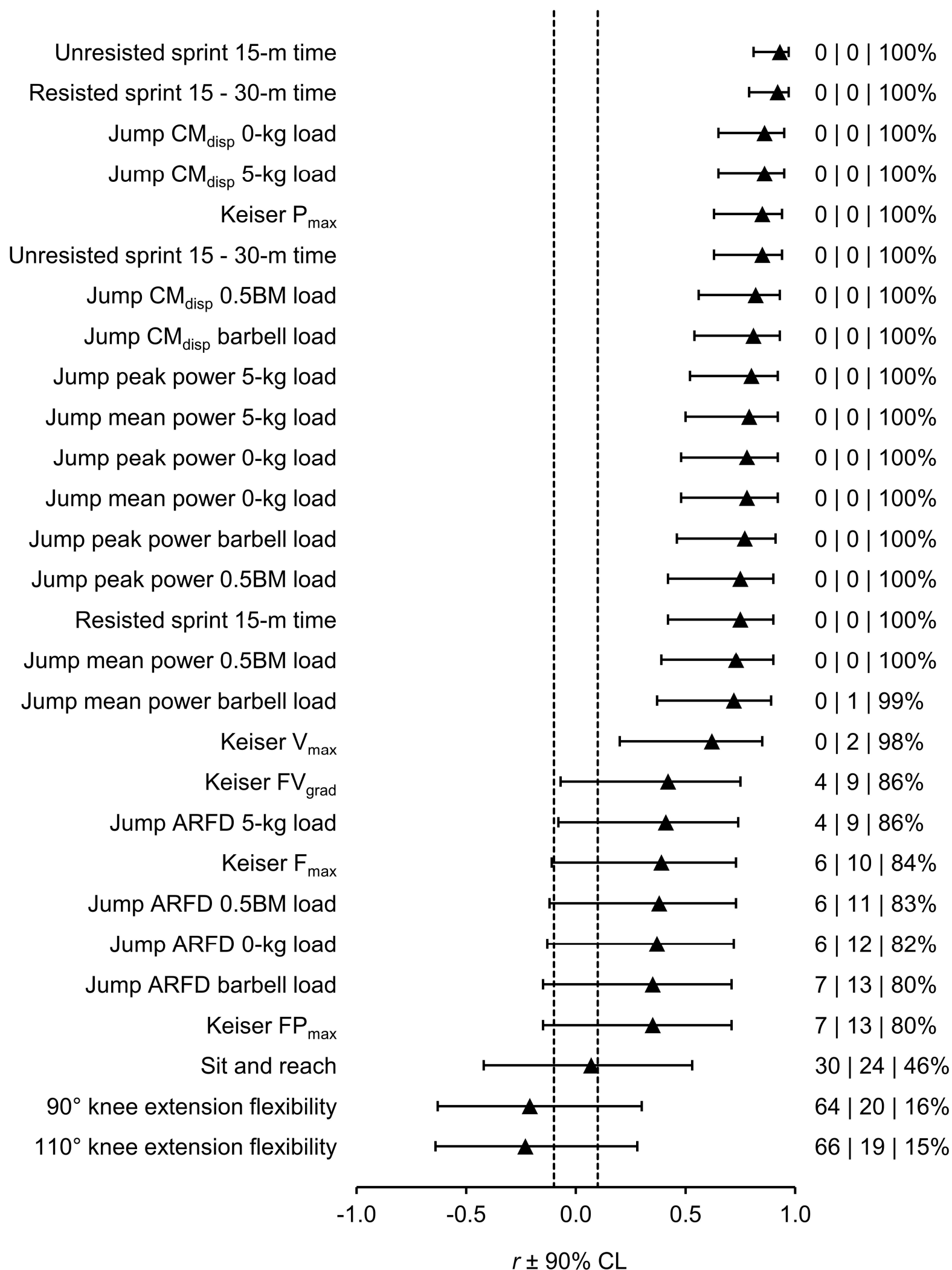
Figure 2. An example of the force-velocity and force-power relationships obtained for one athlete at one time point (values are averaged across legs) and the variables calculated from the leg press testing. Circles and squares indicate raw force-velocity and force-power data, respectively. Solid black lines represent line of best fit through raw data. Extended dashed lines represent data extrapolation to obtain F_{\max} and V_{\max} . Vertical dashed line indicates method used to calculate FP_{\max} from P_{\max} .

Figure 3. Pearson correlation coefficients ($\pm 90\%$ CI) between 15-m sled velocity and physical test scores. N.B. The sprint time coefficients have been inverted for presentation purposes. Central area ($r = -0.1$ to 0.1) indicates a trivial relationship. Percentages represent the likelihoods that the effect is negative | trivial | positive.

Figure 4. Pearson correlation coefficients ($\pm 90\%$ CI) between 38 - 45-m sled velocity and physical test scores. N.B. The sprint time coefficients have been inverted for presentation purposes. Central area ($r = -0.1$ to 0.1) indicates a trivial relationship. Percentages represent the likelihoods that the effect is negative | trivial | positive.







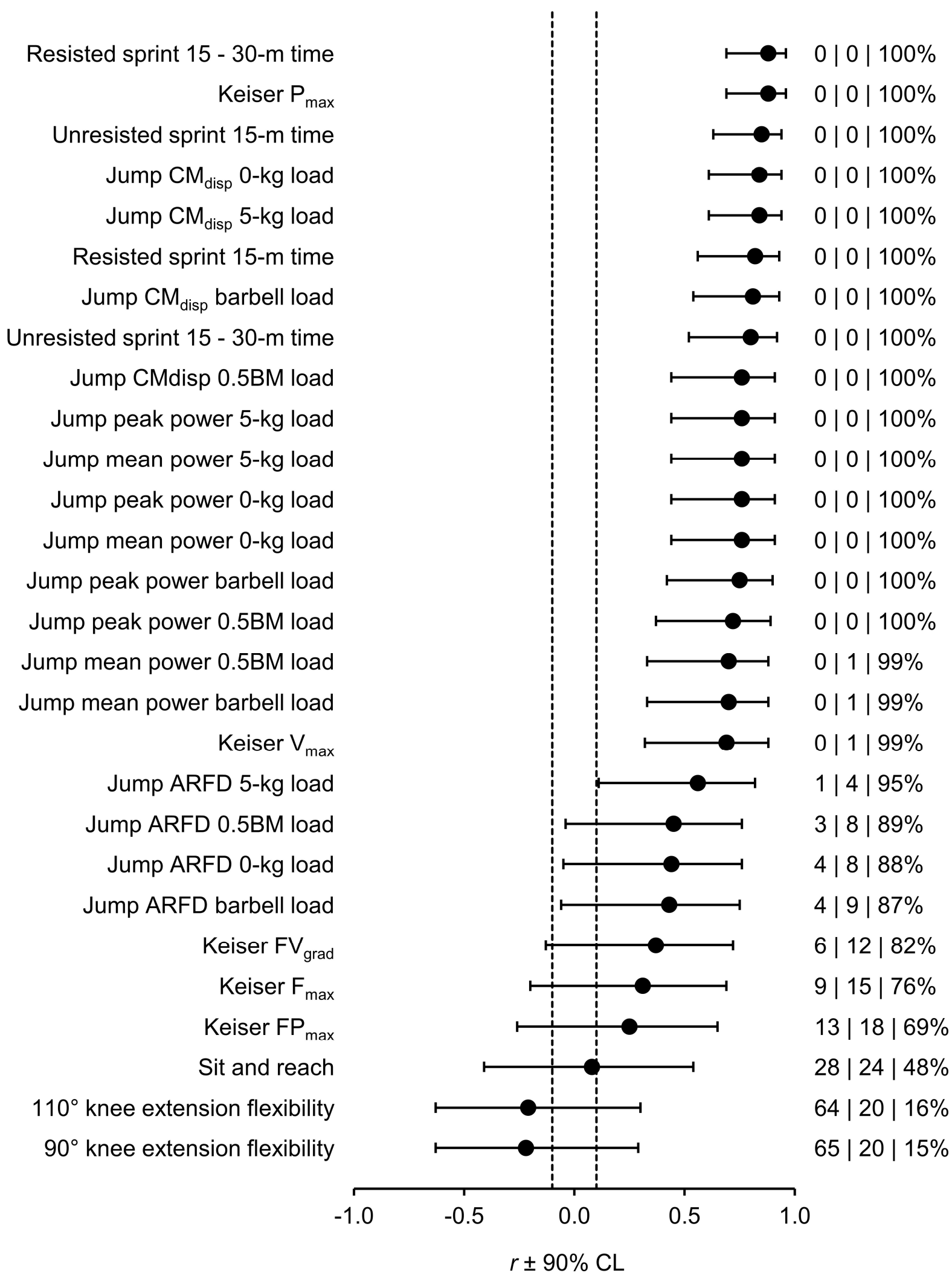


Table 1. Principal component analysis output.

	Component 1	Component 2	Component 3
Variance explained	35.7%	34.5%	27.0%
Unresisted sprint 15-m time	<u>0.869</u>	-0.304	-0.347
Resisted sprint 15 - 30-m time	0.866	-0.121	-0.439
Jump CM _{disp} 0-kg load	-0.507	0.292	<u>0.801</u>
Jump CM _{disp} 5-kg load	-0.558	0.283	0.765
Keiser F _{max}	-0.186	0.942	0.219
Keiser FP _{max}	-0.184	<u>0.954</u>	0.179

N.B. Bold values indicate the component to which each variable was most strongly related to.

Underlined values indicate the variables which were subsequently entered into the multiple regression analysis.

Table 2. Physical test scores (mean \pm SD) achieved by eight male skeleton athletes at each testing session and the overall variability of test scores.

	Baseline	Week 8	Week 12	Week 16	Week 24	Mean CV (%)
15-m sled velocity ($\text{m}\cdot\text{s}^{-1}$)	7.45 ± 0.16	7.39 ± 0.23	7.48 ± 0.28	7.47 ± 0.20	7.54 ± 0.20	1.43
38 - 45-m sled velocity ($\text{m}\cdot\text{s}^{-1}$)	10.58 ± 0.18	10.57 ± 0.24	10.55 ± 0.26	10.59 ± 0.11	10.73 ± 0.28	0.89
Unresisted sprint 15-m time (s)	2.43 ± 0.04	2.47 ± 0.05	2.46 ± 0.07	2.45 ± 0.08	2.38 ± 0.07	1.73
Unresisted sprint 15 - 30-m time (s)	1.66 ± 0.05	1.68 ± 0.05	1.65 ± 0.05	1.68 ± 0.04	1.64 ± 0.05	1.00
Resisted sprint 15-m time (s)	2.79 ± 0.05	2.84 ± 0.11	2.82 ± 0.09	2.74 ± 0.08	2.74 ± 0.08	2.00
Resisted sprint 15 - 30-m time (s)	1.92 ± 0.05	1.98 ± 0.06	1.94 ± 0.07	1.95 ± 0.05	1.93 ± 0.08	1.74
90° knee extension flexibility (°)	153 ± 4	162 ± 5	160 ± 12	168 ± 10	170 ± 4	4.91
110° knee extension flexibility (°)	132 ± 6	137 ± 10	139 ± 7	150 ± 12	156 ± 8	7.39
Sit and reach (cm)	29 ± 6	32 ± 5	34 ± 5	34 ± 3	31 ± 5	8.45
Jump CM_{disp} 0-kg load (m)	0.57 ± 0.05	0.61 ± 0.03	0.62 ± 0.02	0.63 ± 0.04	0.63 ± 0.03	4.35
Jump CM_{disp} 5-kg load (m)	0.57 ± 0.04	0.57 ± 0.04	0.60 ± 0.05	0.60 ± 0.05	0.61 ± 0.04	4.15
Jump CM_{disp} barbell load (m)	0.46 ± 0.07	0.47 ± 0.07	0.49 ± 0.07	0.52 ± 0.07	0.49 ± 0.05	5.73
Jump CM_{disp} 0.5BM load (m)	0.37 ± 0.04	0.39 ± 0.04	0.41 ± 0.03	0.41 ± 0.04	0.41 ± 0.04	4.91
Jump peak power 0-kg load ($\text{W}\cdot\text{kg}^{-1}$)	66.6 ± 5.0	67.6 ± 3.7	68.9 ± 2.5	68.9 ± 4.3	69.6 ± 4.3	3.29
Jump peak power 5-kg load ($\text{W}\cdot\text{kg}^{-1}$)	65.8 ± 4.2	66.7 ± 4.1	68.7 ± 3.7	67.8 ± 4.6	69.1 ± 5.1	3.67
Jump peak power barbell load ($\text{W}\cdot\text{kg}^{-1}$)	62.6 ± 3.6	63.4 ± 3.8	64.8 ± 3.1	65.7 ± 4.6	66.0 ± 4.5	2.66
Jump peak power 0.5BM load ($\text{W}\cdot\text{kg}^{-1}$)	61.6 ± 4.5	62.8 ± 3.9	64.2 ± 2.8	64.2 ± 4.9	65.4 ± 4.7	2.58
Jump mean power 0-kg load ($\text{W}\cdot\text{kg}^{-1}$)	37.8 ± 3.8	37.6 ± 2.9	38.2 ± 2.2	37.8 ± 2.3	37.7 ± 2.3	4.24
Jump mean power 5-kg load ($\text{W}\cdot\text{kg}^{-1}$)	35.8 ± 3.2	35.5 ± 3.2	36.7 ± 2.6	35.9 ± 2.5	34.1 ± 2.0	5.14
Jump mean power barbell load ($\text{W}\cdot\text{kg}^{-1}$)	34.0 ± 2.6	33.9 ± 2.6	34.4 ± 2.2	34.2 ± 2.0	33.5 ± 2.3	3.60
Jump mean power 0.5BM load ($\text{W}\cdot\text{kg}^{-1}$)	32.5 ± 3.0	32.5 ± 2.5	33.4 ± 1.9	32.7 ± 2.2	32.6 ± 2.3	3.54
Jump ARFD 0-kg load ($\text{kN}\cdot\text{s}^{-1}$)	6.92 ± 2.44	6.22 ± 1.83	6.22 ± 2.38	5.48 ± 1.93	4.43 ± 1.53	22.70
Jump ARFD 5-kg load ($\text{kN}\cdot\text{s}^{-1}$)	5.46 ± 2.17	4.97 ± 1.25	4.76 ± 1.94	4.90 ± 1.71	4.22 ± 1.57	24.44
Jump ARFD barbell load ($\text{kN}\cdot\text{s}^{-1}$)	4.71 ± 1.59	3.94 ± 1.89	4.34 ± 2.35	3.73 ± 1.54	2.81 ± 1.31	30.51
Jump ARFD 0.5BM load ($\text{kN}\cdot\text{s}^{-1}$)	3.28 ± 1.41	2.96 ± 1.06	2.96 ± 0.68	2.49 ± 1.20	2.23 ± 0.56	24.41
Keiser F_{max} ($\text{N}\cdot\text{kg}^{-1}$)	67.8 ± 25.4	76.7 ± 5.9	79.7 ± 7.4	86.3 ± 10.5	86.7 ± 10.9	16.10
Keiser V_{max} ($\text{m}\cdot\text{s}^{-1}$)	1.17 ± 0.10	1.10 ± 0.10	1.10 ± 0.10	1.03 ± 0.15	1.07 ± 0.10	6.95
Keiser P_{max} ($\text{W}\cdot\text{kg}^{-1}$)	20.6 ± 1.5	20.8 ± 2.0	21.0 ± 1.8	20.9 ± 1.8	21.2 ± 0.9	3.19
Keiser FP_{max} ($\text{N}\cdot\text{kg}^{-1}$)	37.8 ± 4.8	39.7 ± 4.6	41.9 ± 4.7	44.1 ± 6.1	44.2 ± 6.2	8.54
Keiser FV_{grad} ($\cdot 10^4$)	-2.1 ± 0.3	-1.9 ± 0.2	-1.8 ± 0.3	-1.6 ± 0.3	-1.6 ± 0.3	14.48

Table 3. Physical test scores (mean \pm SD) achieved by five female skeleton athletes at each testing session and the overall variability of test scores

	Baseline	Week 8	Week 12	Week 16	Week 24	Mean CV (%)
15-m sled velocity ($\text{m}\cdot\text{s}^{-1}$)	6.61 ± 0.13	6.84 ± 0.17	6.91 ± 0.18	6.90 ± 0.08	6.90 ± 0.19	1.49
38 - 45-m sled velocity ($\text{m}\cdot\text{s}^{-1}$)	9.84 ± 0.14	10.01 ± 0.14	9.97 ± 0.17	10.00 ± 0.11	10.13 ± 0.19	1.14
Unresisted sprint 15-m time (s)	2.71 ± 0.05	2.68 ± 0.05	2.67 ± 0.04	2.68 ± 0.03	2.67 ± 0.07	1.03
Unresisted sprint 15 - 30-m time (s)	1.86 ± 0.05	1.84 ± 0.03	1.82 ± 0.04	1.85 ± 0.01	1.83 ± 0.06	1.87
Resisted sprint 15-m time (s)	3.17 ± 0.08	3.05 ± 0.09	3.04 ± 0.08	3.05 ± 0.10	3.02 ± 0.13	2.49
Resisted sprint 15 - 30-m time (s)	2.19 ± 0.03	2.15 ± 0.03	2.16 ± 0.06	2.15 ± 0.08	2.14 ± 0.10	2.14
90° knee extension flexibility (°)	151 ± 5	160 ± 17	163 ± 11	172 ± 5	174 ± 1	7.74
110° knee extension flexibility (°)	132 ± 9	135 ± 12	151 ± 12	155 ± 1	157 ± 7	9.23
Sit and reach (cm)	28 ± 4	29 ± 5	28 ± 6	31 ± 6	30 ± 4	8.37
Jump CM_{disp} 0-kg load (m)	0.41 ± 0.05	0.47 ± 0.06	0.50 ± 0.06	0.49 ± 0.07	0.49 ± 0.07	7.56
Jump CM_{disp} 5-kg load (m)	0.39 ± 0.05	0.44 ± 0.05	0.47 ± 0.05	0.47 ± 0.07	0.47 ± 0.06	7.09
Jump CM_{disp} barbell load (m)	0.36 ± 0.05	0.38 ± 0.06	0.39 ± 0.05	0.40 ± 0.07	0.40 ± 0.05	6.97
Jump CM_{disp} 0.5BM load (m)	0.29 ± 0.03	0.31 ± 0.04	0.30 ± 0.03	0.31 ± 0.04	0.31 ± 0.05	5.51
Jump peak power 0-kg load ($\text{W}\cdot\text{kg}^{-1}$)	54.7 ± 4.2	56.0 ± 6.5	57.6 ± 6.2	57.7 ± 6.7	57.8 ± 6.9	3.64
Jump peak power 5-kg load ($\text{W}\cdot\text{kg}^{-1}$)	53.1 ± 4.6	55.1 ± 5.8	57.5 ± 5.2	56.6 ± 6.0	57.1 ± 6.3	4.35
Jump peak power barbell load ($\text{W}\cdot\text{kg}^{-1}$)	51.9 ± 3.8	52.0 ± 5.6	55.1 ± 5.8	55.0 ± 6.9	54.7 ± 6.4	4.30
Jump peak power 0.5BM load ($\text{W}\cdot\text{kg}^{-1}$)	50.6 ± 4.3	50.7 ± 5.8	53.7 ± 5.9	53.1 ± 6.7	53.4 ± 6.9	4.51
Jump mean power 0-kg load ($\text{W}\cdot\text{kg}^{-1}$)	31.8 ± 2.9	30.9 ± 3.7	32.0 ± 3.3	31.1 ± 3.7	31.8 ± 3.8	3.29
Jump mean power 5-kg load ($\text{W}\cdot\text{kg}^{-1}$)	29.2 ± 3.3	28.9 ± 3.1	30.1 ± 2.6	28.4 ± 3.8	29.5 ± 3.0	4.33
Jump mean power barbell load ($\text{W}\cdot\text{kg}^{-1}$)	28.1 ± 3.4	26.2 ± 4.2	28.9 ± 2.9	28.1 ± 4.1	28.1 ± 3.5	5.89
Jump mean power 0.5BM load ($\text{W}\cdot\text{kg}^{-1}$)	25.9 ± 3.9	25.0 ± 2.8	26.6 ± 3.3	26.3 ± 4.6	26.1 ± 3.7	4.88
Jump ARFD 0-kg load ($\text{kN}\cdot\text{s}^{-1}$)	6.60 ± 1.21	5.02 ± 1.37	4.81 ± 1.27	3.87 ± 2.07	4.89 ± 1.31	28.00
Jump ARFD 5-kg load ($\text{kN}\cdot\text{s}^{-1}$)	6.01 ± 1.75	2.88 ± 1.06	3.85 ± 1.76	2.49 ± 0.84	3.77 ± 1.41	48.78
Jump ARFD barbell load ($\text{kN}\cdot\text{s}^{-1}$)	4.24 ± 2.17	2.38 ± 0.90	2.38 ± 0.89	2.11 ± 0.83	2.28 ± 0.80	32.12
Jump ARFD 0.5BM load ($\text{kN}\cdot\text{s}^{-1}$)	2.30 ± 1.20	1.86 ± 0.88	1.99 ± 0.93	1.56 ± 0.28	1.70 ± 0.53	16.14
Keiser F_{max} ($\text{N}\cdot\text{kg}^{-1}$)	62.3 ± 5.3	67.5 ± 2.7	68.8 ± 4.2	69.6 ± 5.4	72.7 ± 7.4	6.66
Keiser V_{max} ($\text{m}\cdot\text{s}^{-1}$)	1.08 ± 0.16	0.98 ± 0.12	0.97 ± 0.08	0.98 ± 0.13	0.92 ± 0.12	6.29
Keiser P_{max} ($\text{W}\cdot\text{kg}^{-1}$)	15.8 ± 1.6	16.3 ± 1.4	16.2 ± 1.1	16.3 ± 2.2	16.6 ± 1.9	4.63
Keiser FP_{max} ($\text{N}\cdot\text{kg}^{-1}$)	31.5 ± 3.3	33.6 ± 0.7	34.7 ± 2.3	34.9 ± 3.2	36.9 ± 3.8	7.14
Keiser FV_{grad} ($\cdot 10^4$)	-2.6 ± 0.5	-2.2 ± 0.3	-2.1 ± 0.3	-2.1 ± 0.3	-1.9 ± 0.3	11.65